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13. Abstract ***(Maximum 200 Words)*** *(abstract should contain no proprietary or confidential information)*

This project is a research effort that helps define thermal infrared (IR) imaging as a diagnostic tool in early detection of breast cancer, which can be used as a complementary to traditional mammography. One of the popular methods for breast cancer detection is to make comparisons between contralateral images. In IR imaging, asymmetry analysis normally needs human interference because of the difficulties in automatic segmentation. In order to provide a more objective diagnosis result, we proposed an automatic approach to asymmetry analysis in thermograms. It includes automatic segmentation and pattern classification. The segmentation algorithm uses Hough transform coupled with Canny edge detector to identify four feature curves that define the segments. We propose two pattern classification algorithms, unsupervised clustering and supervised learning based on feature extraction. Experiments have been conducted using images provided by Elliott Mastology Center (Inframetrics 600M camera) and Bioyear, Inc. (Microbolometer uncooled camera). Experimental results show that feature extraction provides a valuable signature for asymmetry identification. With a larger database, supervised pattern classification techniques can be used to attain more accurate classification.

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Table of Contents

1 Introduction

This project is a research effort that helps define thermal infrared (IR) imaging as a diagnostic tool in early detection of breast cancer, which can be used as a complementary to traditional mammography. One of the popular methods for breast cancer detection is to make comparisons between contralateral images. When the images are relatively symmetrical, small asymmetries may indicate a suspicious region. In IR imaging, asymmetry analysis normally needs human interference because of the difficulties in automatic segmentation. In order to provide a more objective diagnosis result, we proposed an automatic approach to asymmetry analysis in thermograms. It includes automatic segmentation and supervised pattern classification. Experiments have been conducted based on images provided by Elliott Mastology Center (Inframetrics 600M camera) and Bioyear, Inc. (Microbolometer uncooled camera).

2 Body

The application of IR imaging in breast cancer study starts as early as 1961 when Williams and Handley first published their results in the *Lancet* [11]. However, the premature use of the technology and its poorly controlled introduction into breast cancer detection in the 70s have led to its early demise [9]. IR-based diagnosis was criticized to generate a higher false-positive rate than mammogram, and thus was not recommended as a standard modality for breast cancer detection. Therefore, despite its deployment in many areas of industry and military, IR usage in medicine has declined [8]. Three decades later, several papers and studies have been published to reappraise the use of IR in medicine [9, 8] for the following three reasons: 1) We have much more improved infrared technology. New generations of IR cameras have been developed with much enhanced accuracy; 2) We have much better capabilities in image processing. Advanced techniques including image enhancement, restoration and segmentation have been effectively used in processing IR images; and 3) We have a deeper understanding of IR images based on the patho-physiological approach.

The main objective of this work is to evaluate the viability of IR imaging as a non-invasive imaging modality for early detection of breast cancer so that it can be performed both on the symptomatic and asymptomatic patients and can thus be used as a complementary to traditional mammography. This report summarizes how the identification of the asymmetry can be automated using the image segmentation, feature extraction and pattern recognition techniques. We investigate different features that contribute the most towards the detection of asymmetry. This kind of approach would help reduce the false positive rate of the diagnosis and increase chances of disease cure and survival.

2.1 Background Study

2.1.1 Measuring the Temperature of Human Body

Temperature is a long established indicator of health. The Greek physician, Hippocrates, wrote in 400 B.C. "In whatever part of the body excess of heat or cold is felt, the disease is there to be discovered [16]." The ancient Greeks immersed the body in wet mud and the area that dried more quickly, indicating a warmer region, was considered the diseased tissue. The use of hands to measure heat-emanating form the body remained well into the sixteenth and the seventeenth centuries. It wasn't until Galileo, who made a thermoscope from a glass tube, that some form of the temperature sensing device was developed, but it did not have a scale. It is Fahrenheit and later Celsius who have fixed the temperature scale and proposed the present day clinical thermometer. The use of liquid crystals is another method of displaying skin temperature. Cholesteric esters can have the property of changing colors with temperature and this was established by Lehmann in 1877. It was involved in use of elaborative panels that encapsulated the crystals and were applied to the surface of the skin, but due to large area of contact, they affected the temperature of the skin. All the methods discussed above are contact based.

Major advances over the past 30 years have been with infrared (IR) thermal imaging. The astronomer, Sir William Herschel, in Bath, England discovered the existence of infrared radiation by trying to measure the heat of the separate colors of the rainbow spectrum cast on a table in the darkened room. He found the highest temperature appear beyond the red end of the spectrum. He reported to the Royal society as Dark Heat in 1800, which is eventually the Infrared portion of the spectrum. Infrared radiation occupies the region between visible and microwaves. All objects in the universe emit radiations in the IR region of the spectra as a function of their temperature. As an object gets hotter, it gives off more intense infrared radiation, and it radiates at a shorter wavelength [8]. At moderate temperatures (above 200°F), the intensity of the radiation gets high enough so that the human body can detect that radiation as heat. At high enough temperatures (above 1200°F), the intensity gets high enough and the wavelength gets short enough so that the radiation crosses over the threshold to the red end of the visible light spectrum. Human eye cannot detect IR rays, but they can be detected by using the thermal infrared cameras and detectors.

2.1.2 Metabolic Activity of Human Body and Cancer Cells

Metabolic process in a cell can be briefly defined as the sum total of all the enzymatic reactions occurring in the cell. It can be further elaborated as a highly coordinated, purposeful activity in which many sets of interrelated multi enzyme systems participate exchanging both matter and energy between the cell and its environment. Metabolism has four specific functions: 1) To obtain chemical energy from the fuel molecules; 2) To convert exogenous nutrients into the building blocks or precursor of macromolecular cell components; 3) To assemble such building blocks into proteins, nucleic acids, lipids and other cell components; and 4) To form and degrade biomolecules required in specialized functions of the cell.

Metabolism can be divided into two major phases, Catabolism and Anabolism. Catabolism is the degradative phase of metabolism in which relatively large and complex nutrient molecules

(carbohydrates, lipids and proteins) are degraded to yield smaller, simpler molecules such as lactic acid, acetic acid, CO_2, ammonia or urea. Catabolism is accompanied by conservation of some of the energy of the nutrient in the form of phosphate bond energy of adenosine triphosphate (ATP). Conversely, Anabolism is the building up phase of metabolism, the enzymatic biosynthesis of such molecular components of such molecular components of cells as nucleic acids, proteins, lipids and carbohydrates from their simple building block precursors. Biosynthesis of organic molecules form simple precursors requires input of chemical energy which is furnished by ATP generated during catabolism. Each of these pathways is promoted by a sequence of specific enzymes catalyzing consecutive reactions. The energy produced by the metabolic pathways is utilized by the cell for its division. Cells undergo mitotic cell division, a process in which a single cell divide into many cells, and into tissues and further into the growth of the multicellular organs. When cells divide, each resultant part is a complete relatively small cell. Immediately after division the newly formed cells grow rapidly soon reaching the size of the original cell. In humans, growth occurs through mitotic cell division with subsequent enlargement and differentiation of the reproduced cells into organs. Cancer cells also grow similarly but lose the ability to differentiate into organs. So, cancer cells are defined as actively dividing undifferentiated mass of cells called tumors.

Cancer cells result from permanent genetic change in a normal cell triggered by some external physical agents such as chemical agents, X-rays, UV rays, etc. They tend to grow aggressively and do not obey normal pattern of tissue formation. Cancer cells have a distinctive type of metabolism. Although they possess all the enzymes required for most of the central pathways of metabolism, cancer cells of nearly all types show an anomaly in the glucose degradation pathway (viz. Glycolysis). The rate of oxygen consumption is somewhat below the values given by normal cells. However the malignant cells tend to utilize anywhere from 5-10 times as much glucose as normal tissue and convert most of it into lactate instead of pyruvate (lactate is a low energy compound whereas pyruvate is a high energy compound). The net effect is that in addition to the generation of ATP in mitochondria from respiration, there is a very large formation of ATP in extramitochondrial compartment from glycolysis. The most important effect of this metabolic imbalance in cancer cells is the utilization of a large amount of blood glucose and release large amounts of lactate into blood. The lactate so formed is recycled in the liver to produce blood glucose again. Since the formation of blood glucose by the liver requires 6 molecules of ATP whereas breakdown of glucose to lactate produces only 2 ATP molecules, the cancer cells are looked upon as metabolic parasites dependent on the liver for a substantial part of energy. Large masses of cancer cells thus can be a considerable metabolic drain on the host organism. In addition to this, the high metabolic rate of cancer cells causes an increase in local temperature as compared to normal cells. Local metabolic activity ceases when blood supply is stopped since glycolysis is an oxygen dependent pathway and oxygen is transported to the tissues by the hemoglobin present in the blood, thus blood supply to these cells is important for them to proliferate. The growth of a solid tumor is limited by the blood supply. If it were not invaded by capillaries a tumor would be dependent on the diffusion of nutrients from its surroundings and could not enlarge beyond a diameter of a few mm. In contrast to this, to grow further the tumor cells stimulate the blood vessels to form a capillary network that invades the tumor mass. This phenomenon is popularly called as angiogenesis which is a process of vascularization of a tissue involving the development of new capillary blood vessels.

Vascularization is a growth of blood vessels into a tissue with the result that the oxygen and

nutrient supply is improved. Vascularization of tumors is usually a prelude to more rapid growth and often to metastasis (advanced stage of cancer). Vascularization seems to be triggered by angiogenesis factors that stimulate endothelial cell proliferation and migration. In context to this paper the high metabolic rate in the cancer cells and the high density of packaging makes it a key source of heat concentration (since the heat dissipation is low) thus enabling thermal infrared imaging as a viable technique to visualize the abnormality.

2.1.3 Early Detection of Breast Cancer

There is a crucial need for early breast cancer detection. Research has shown that if detected earlier (tumor size less than 10mm), the breast cancer patient has an 85% chance of cure as opposed to 10% if the cancer is detected late [12].

Different kinds of diagnostic imaging techniques exist in the field of breast cancer detection. The most popularly used method presently is X-ray mammography. The drawback of this technique is that it is invasive and experts believe that electromagnetic radiations can also be a triggering factor for cancerous growth. Because of this, periodic inspection might have a negative effect on the patient's health. Research shows that the mammogram sensitivity is higher for older women (age group 60-69 years) at 85% compared with younger women (<50 years) at 64% [12]. A new study in a British medical journal (The LANCET [14]) has asserted that there is no reliable evidence that screening with mammography for breast cancer reduces mortality. They show that screening actually leads to more aggressive treatment, increasing the number of mastectomies by about 20% and the number of mastectomies and tumorectomies by about 30%.

In contrast to this IR imaging uses a non-invasive imaging technique as the diagnostic tool. The main source of infrared rays is heat emitted from different bodies whose temperature is above absolute zero. Thus a thermogram of a patient provides the heat distribution in the body. The cancerous cells, due to high metabolic rates, are at a higher temperature than the normal cells around it. Thus the cancer cells can be imaged as hotspots in the infrared images. The thermogram provides more dynamic information of the tumor since the tumor can be small in size but can be fast growing making it appear as a high temperature spot in the thermogram [5, 17]. However, this is not the case in mammography, in which unless the tumor is beyond certain size, it cannot be imaged as X-rays essentially pass through it unaffected. This qualifies IR imaging as an effective diagnostic tool for early detection of breast cancer. Keyserlingk *et al.* [9] reported that the average tumor size undetected by thermal imaging is 1.28cm and 1.66cm by mammography. It is also reported that the results of thermography can be correct 8-10 years before mammography can detect a mass in the patient's body [3, 13].

2.2 Asymmetric Analysis in Breast Cancer Detection

Making comparisons between contralateral images are routinely done by radiologists. When the images are relatively symmetrical, small asymmetries may indicate a suspicious region. This is the underlying philosophy in the use of asymmetry analysis for mass detection in breast cancer study [4]. Unfortunately, due to various reason like short of radiologists, fatigue, carelessness, or simply

because of the limitation of human visual system, these small asymmetries might not be easy to detect. Therefore, it is important to design an automatic approach to eliminate human factors.

There have been a few papers addressing techniques for asymmetry analysis of mammograms [4, 15, 18, 19, 20, 21]. [6, 10] recently analyzed the asymmetric abnormalities in infrared images. In their approach, the thermograms are segmented first by operator. Then breast quadrants are derived automatically based on unique point of reference, i.e. the chin, the lowest, rightmost and leftmost points of the breast.

This project proposed an automatic approach to asymmetry analysis in thermograms. It includes automatic segmentation and pattern classification. Hough transform is used to extract the four feature curves that can uniquely segment the left and right breasts. The feature curves include the left and the right body boundary curves, and the two parabolic curves indicating the lower boundaries of the breasts. Upon segmentation, different pattern recognition techniques are applied to identify the asymmetry.

Both segmentation and classification results are shown on images provided by Elliott Mastology Center (Inframetrics 600M camera) and Bioyear, Inc. (Microbolometer uncooled camera).

2.2.1 Automatic Segmentation

Edge image is first derived by using Canny edge detector [1]. The standard deviation is chosen to be equal to 2.5 so that only strong edges are detected.

There are four dominant curves appeared in the edge image which we called the feature curves: the left and right body boundaries, and two lower boundaries of the breasts. The body boundaries are easy to detect. Difficulties lie in the detection of the lower boundaries of the breasts. We observe that the breast boundaries are generally in parabolic shape. Therefore, Hough transform [7] is used to detect the parabola.

Segmentation is based on three key points: the two armpits (P_L, P_R) derived from the left and right body boundaries by picking up the point where the largest curvature occurs, and the intersection (O) of the two parabolic curves derived from the lower boundaries of the breasts. The vertical line that goes through point O and is perpendicular to line P_LP_R is the one used to separate the left and right breasts.

The first set of testing images are obtained using the Inframetrics 600M camera, with a thermal sensitivity of 0.05^0K. The image are collected at Elliott Mastology Center. Results from two testing images (lr, nb) are shown in Figure 1, that includes the intermediate results from edge detection, feature curve extraction, to segmentation. From the figure, we can see that Hough transform can derive the parabola at the accurate location.

Another set of images are obtained using Microbolometer uncooled camera, with a thermal sensitivity of 0.05^0K. Some examples of the segmented images are shown in Figure 2.

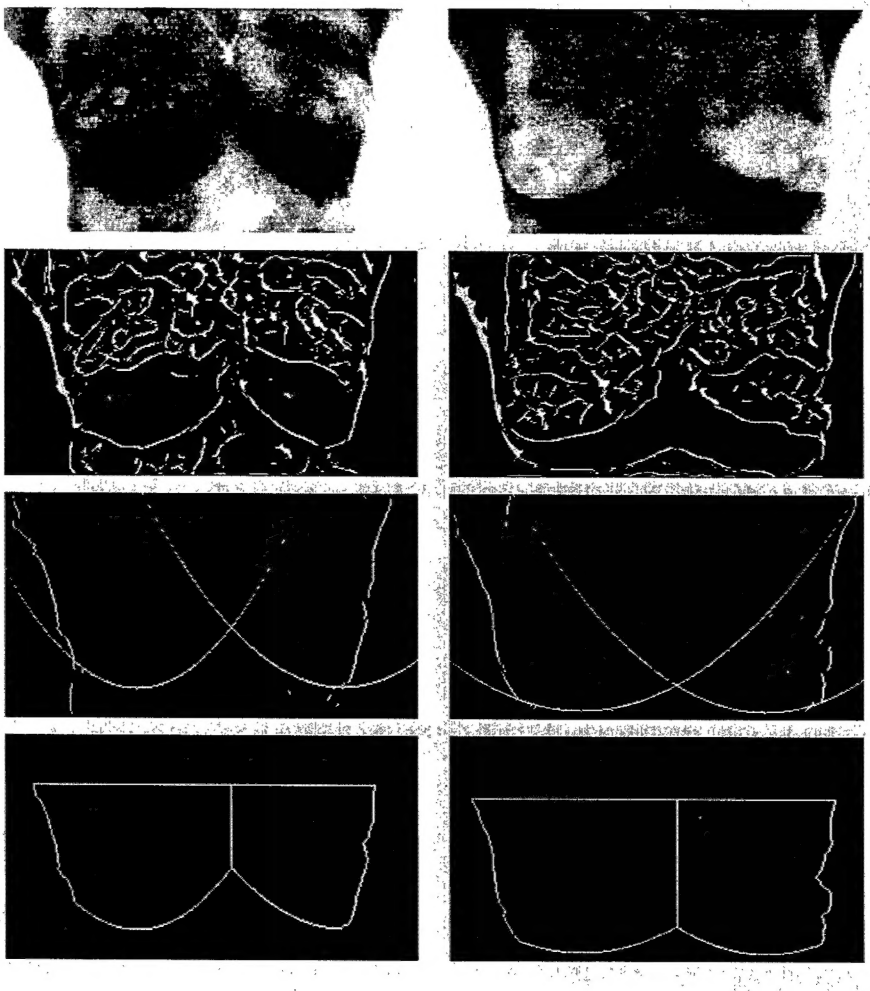

Figure 1: Segmentation results of two images. Left: results from lr. Right: results from nb. From top to bottom: original image, edge image, four feature curves, segments.

2.2.2 Asymmetry Identification by Unsupervised learning

Pixel values in a thermogram represent the thermal radiation resulting from the heat emanates from the human body. Different tissues, organs and vessels have different amount of radiation. Therefore, by observing the heat pattern, or in another word, the pattern of the pixel value, we should be able to discover the abnormalities if there are any.

Usually, in pattern classification algorithms, a set of training data are given to derive the decision rule. All the samples in the training set have been correctly classified. The decision rule is then applied to the testing data set where samples have not been classified yet. This classification technique is also called supervised learning. In unsupervised learning, however, data sets are not divided into training sets or testing sets. No *a-priori* knowledge is known about which class each sample belongs to.

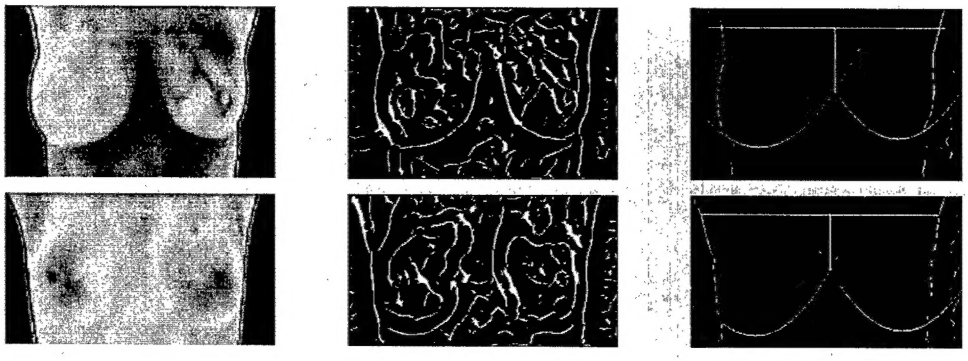

Figure 2: Hough transform based image segmentation. Top: segments of a cancerous image. Bottom: segments of a non-cancerous image. From left to right: the original TIR image, the edge image using Canny edge detector, the segmentation based on Hough transform.

In asymmetry analysis, none of the pixels in the segment knows its class in advance, thus there will be no training set or testing set. Therefore, this is an unsupervised learning problem. We use k-means algorithm to do the initial clustering. k-means algorithm is described as follows:

1. Begin with an arbitrary set of cluster centers and assign samples to nearest clusters;
2. Compute the sample mean of each cluster;
3. Reassign each sample to the cluster with the nearest mean;
4. If the classification of all samples has not changed, then stop, else go to step 2.

After each sample is relabeled to a certain cluster, the cluster mean can then be calculated. The segmented image can also be displayed in labeled format. From the difference of mean distribution, we can tell if there is any asymmetric abnormalities.

Figure 3 provides the histogram of pixel value from each segment that generated in Figure 1 with 10-bin setup. We can tell just from the shape of the histogram that lr shows a more apparent abnormalities than nb. However, histogram only reveals global information. Figure 4 displays the classification results for each segment in its labeled format. Here, we choose to use four clusters. The figure also shows the mean difference of each cluster in each segmented image. From Fig. 4, we can clearly see the much bigger difference shown in the mean distribution or image lr which can also be observed from the labeled image.

2.2.3 Asymmetry Identification Using Supervised Learning based on Feature Extraction

Feature extraction is performed on the segmented images. The aim of this research is to identify the effectiveness of the features in contributing towards the asymmetry analysis.

As discussed earlier, TIR imaging is a functional imaging technique representing thermal information as a function of intensity. The TIR image is essentially a pseudo-colored image with a different color assigned to different degree of temperature.

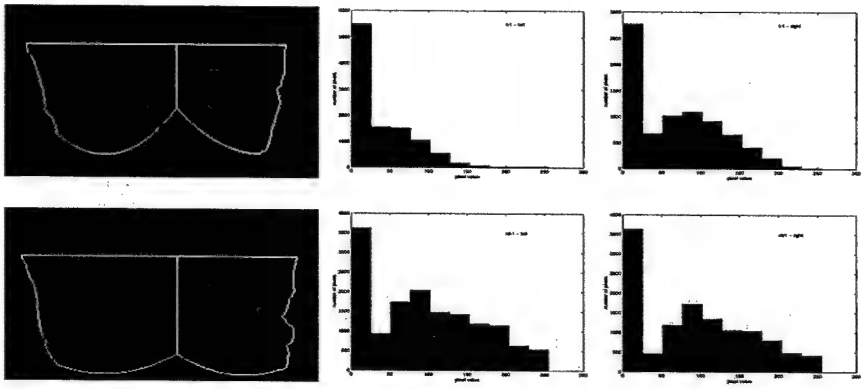

Figure 3: Histogram of the left and right segments. Top: results from lr. Bottom: results from nb. From left to right: the segments, histogram of the left segment, histogram of the right segment.

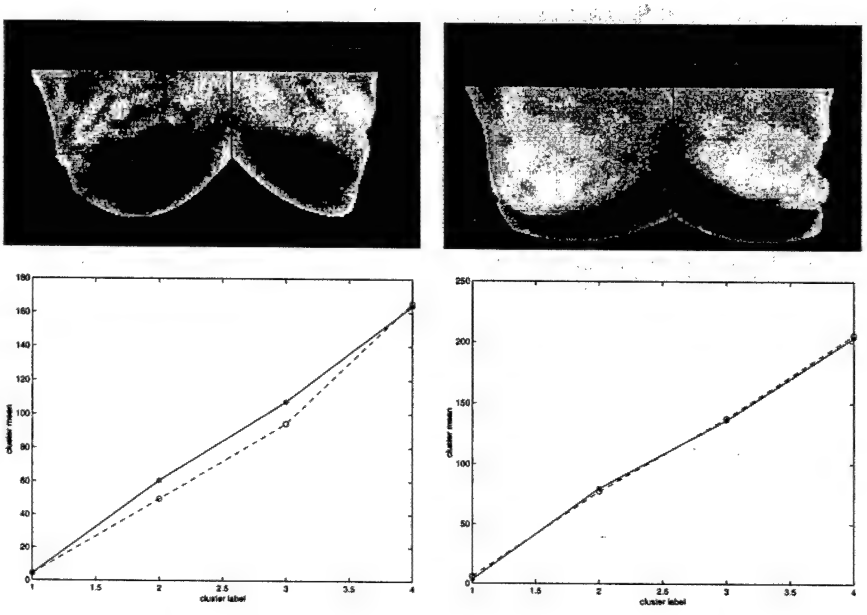

Figure 4: Labeled image and the profile of mean for each cluster. Left: results from lr. Right: results from nb. Top: labeled image. Bottom: average pixel value profile of each cluster

The distribution of different intensities can now be quantified by calculating some high-order statistics as feature elements. We design the following features to form the feature space:

- *Moments of the intensity image*: The intensity component of the image directly corresponds to the thermal energy distribution in the respective areas. The histogram describing the intensity distributions essentially describes the texture of the image. The moments of the histogram gives the statistical information of the texture of the image. Figure 3 shows the intensity distribution of the cancerous and non-cancerous images. The four moments, mean, variance, skewness, and kurtosis are taken as

$$\text{Mean } \mu = \frac{1}{N}\sum_{j=1}^{N} p_j \tag{1}$$

$$\text{Variance } \sigma^2 = \frac{1}{N-1}\sum_{j=1}^{N}(p_j - \mu)^2 \tag{2}$$

$$\text{Skewness } = \frac{1}{N}\sum_{j=1}^{N}[\frac{p_j - \mu}{\sigma}]^3 \tag{3}$$

$$\text{Kurtosis } = \frac{1}{N}\sum_{j=1}^{N}(\frac{p_j - \mu}{\sigma})^4 \tag{4}$$

  where p_j is the probability density of the jth bin in the histogram, and N is the total number of bins.

- *The peak pixel intensity of the correlated image*: The correlated image between the left and right breasts is also a good indication of asymmetry. We use the peak intensity of the correlated image as a feature element since the higher the correlation value, the more symmetric the two breast segments.

- *Entropy*: It measures the uncertainty or the information contained in the segmented images. The more equal the intensity distribution, the more information. Therefore, the segment with hot spots should have a lower Entropy.

$$\text{Entropy } H(X) = -\sum_{j=1}^{N} p_j \log p_j \tag{5}$$

- *Joint Entropy*: The higher the joint entropy between the left and right breast segments, the more symmetric they are supposedly to be, and the less possible of the existence of tumor.

$$\text{Joint Entropy} H(X,Y) = \sum_{i=1}^{N_X}\sum_{j=1}^{N_Y} p_{ij} log(p_{ij}) \tag{6}$$

where p_{ij} is the joint probability density, N_X and N_Y are the number of bins of the intensity histogram of images X and Y respectively .

From the above set of features derived from the testing images, the existence of asymmetry is decided by calculating the ratio of the feature from the left segment to the feature from the right segment. The closer the value to 1, the more correlated the features or the less asymmetric the segments. Classic pattern classification techniques like the maximum posterior probability and the kNN classification [2] can be used for the automatic classification of the images.

Figure 5 shows the 3-D histogram of the thermal distribution described in the intensity component of the cancerous (*ca*) and non-cancerous (*nm*) images. From the graphs, we observe that the *ca* image is more asymmetrical than the *nm* image. This asymmetry can be quantified by calculating the statistical moments of the thermograms. Four moments of this histogram are derived to describe the texture of the image. Table 1 describes the typical moments for the cancerous and non-cancerous images.

Figure 5: The left figure show the intensity distribution of a cancerous image and the right figure shows the same for a non-cancerous image. The cancerous image is more asymmetrical than the non-cancerous one.

Moments	*cancerous*		*non-cancerous*	
	Left	Right	Left	Right
Mean	0.0010	0.0008	0.0012	0.0010
Variance (10^{-6})	2.0808	1.1487	3.3771	2.7640
Skewness (10^{-6})	2.6821	1.1507	4.8489	4.5321
Kurtosis (10^{-8})	1.0481	0.3459	2.1655	2.3641

Table 1: Moments of the histogram.

Other features include the peak correlation coefficient, Entropy, and mutual information. The typical values of the cancerous images and non-cancerous images are tabulated in Table 2. The asymmetry can be clearly stated with a close observation of the above feature values. We used 6 normal patient thermograms and 18 cancer patient thermograms. With a larger database, a trainig feature set can be derived and supervised learning algorithms like discriminant function or k-NN classification can be implemented for a fast, effective, and automated classification.

Figure 6 evaluates the effectiveness of the features used. The first data point along the x-axis indicates *entropy*, the second to the fifth points indicate the four statistical moments (*means,*

Feature	*cancerous*		*non-cancerous*	
Correlation	$\times 10^8$		2.35719×10^8	
Joint Entropy	9.0100		17.5136	
Entropy	Left	Right	Left	Right
	1.52956	1.3033	1.70684	1.4428

Table 2: Entropy and correlation values.

variance, skewness, and kurtosis). The y-axis shows the *closeness* metric we defined as

$$\text{Bilateral ratio closeness to 1} = |\frac{\text{feature value from left segment}}{\text{feature value from right segment}} - 1| \quad (7)$$

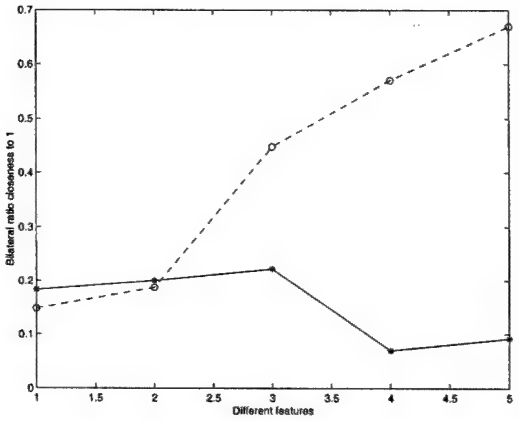

Figure 6: Performance evaluation of different feature elements. Solid line: non-cancerous image; Dash line: cancerous image. The five data points along the x-axis indicate (from left to right): entropy, mean, variance, skewness, kurtosis.

From the figure, we observe that, the high-order statistics are the most effective features to measure the asymmetry, while low-order statistics (*mean*) and *entropy* do not assist asymmetry detection.

3 Key Research Accomplishment

- To the best of our knowledge, this project is the first effort in the design of automatic segmentation algorithm in TIR images for breast cancer detection. We use Hough transform coupled with Canny edge detector to identify four feature curves used to segment the breasts.
- Upon segmentation, we developed different pattern recognition techniques to identify the asymmetry. We proposed two approaches, including the unsupervised learning and feature comparison. Although feature comparison shows advantageous over unsupervised learning, it needs a good training set in order to achieve high accuracy.

- The proposed algorithms have been implemented and evaluated on two independent data sets: images provided by Elliott Mastology Center (Inframetrics 600M camera) and Bioyear, Inc. (Microbolometer uncooled camera).

4 Reportable Outcomes

- Manuscripts

  1. P. T. Kuruganti, H. Qi, "Asymmetry analysis in breast cancer detection using thermal infrared images," *EMBS-BMES*, October 2002.
  2. H. Qi, Z. Qi, C. Wang, "Breast cancer identification through shape analysis in thermal texture maps," *EMBS-BMES*, October 2002.
  3. H. Qi, P. T. Kuruganti, Z. Liu, "Early detection of breast cancer using thermal texture maps," *IEEE International Symposium on Biomedical Imaging: Macro to Nano*, Washington, D. C., July, 2002.
  4. H. Qi, "Feature selection and kNN fusion in molecular classification of multiple tumor types," *International Conference on Mathematics and Engineering Techniques in Medicine and Biological Sciences (METMBS)*, Las Vegas, June, 2002.
  5. H. Qi, J. F. Head, "Asymmetry analysis using automatic segmentation and classification for breast cancer detection in thermograms," *IEEE Engineering in Medicine and Biology Society Annual Conference (EMBS)*, Istanbul, Turkey, October, 2001.

- Abstracts

  1. H. Qi, "Detecting breast cancer from thermal infrared images by asymmetry analysis," *Era of Hope, Department of Defense Breast Cancer Research Program Meeting*, vol. 1, page P15-10, Orlando, FL, September 25-28, 2002.

- Presentations

  1. P. T. Kuruganti, H. Qi, "Asymmetry analysis in breast cancer detection using thermal infrared images," *EMBS-BMES*, October 2002.
  2. H. Qi, Z. Qi, C. Wang, "Breast cancer identification through shape analysis in thermal texture maps," *EMBS-BMES*, October 2002.
  3. H. Qi, P. T. Kuruganti, "Detecting Breast Cancer from Thermal Infrared Images by Asymmetry Analysis," *Era of Hope*, Department of Defense Breast Cancer Research Program Meeting, Orlando, FL, September 25-28, 2002.
  4. H. Qi, P. T. Kuruganti, Z. Liu, "Early detection of breast cancer using thermal texture maps," *IEEE International Symposium on Biomedical Imaging: Macro to Nano*, Washington, D. C., July, 2002.
  5. H. Qi, "Feature selection and kNN fusion in molecular classification of multiple tumor types," *International Conference on Mathematics and Engineering Techniques in Medicine and Biological Sciences (METMBS)*, Las Vegas, June, 2002.

6. H. Qi, Z. Liu, "Use of Thermal Texture Maps (TTM) in Breast Cancer Detection - Bioyear Concept," *From Tanks to Tumors: A Workshop on the Applications of IR Imaging and Automatic Target Recognition (ATR) Image Processing for Early Detection of Breast Cancer*, Arlington, VA, December 4-6, 2001.

7. H. Qi, J. F. Head, "Asymmetry analysis using automatic segmentation and classification for breast cancer detection in thermograms," *IEEE Engineering in Medicine and Biology Society Annual Conference (EMBS)*, Istanbul, Turkey, October, 2001.

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  1. Phani Teja Kuruganti, M.S. Student, Expected: May 2003.

5 Conclusions

This project develop a computer-aid approach for automating the asymmetry analysis of the thermograms. This kind of approach will help the diagnostics as a useful second opinion. The use of TIR images for breast cancer detection and the advantages of thermograms over traditional mammograms are studied. From the experimental results, it can be observed that the Hough transform can be effectively used for breast segmentation. We propose two pattern classification algorithms, the unsupervised learning using kmeans and the supervised learning using kNN based on feature extraction. Experimental results show that feature extraction is a valuable approach to extract the signatures of asymmetry, especially the joint entropy. With a larger database, supervised pattern classification techniques can be used to attain more accurate classification. These kind of diagnostic aids, especially in a diseases like breast cancer where the reason for the occurrence is not totally known, will reduce the false positive diagnosis rate and increase the survival rate among the patients since the early diagnosis of the disease is more curable than in a later stage.

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6 Appendices

1. P. T. Kuruganti, H. Qi, "Asymmetry analysis in breast cancer detection using thermal infrared images," *EMBS-BMES*, October 2002. (page 16-17)

2. H. Qi, Z. Qi, C. Wang, "Breast cancer identification through shape analysis in thermal texture maps," *EMBS-BMES*, October 2002. (page 18-19)

3. H. Qi, "Detecting breast cancer from thermal infrared images by asymmetry analysis," *Era of Hope, Department of Defense Breast Cancer Research Program Meeting*, vol. 1, page P15-10, Orlando, FL, September 25-28, 2002. (page 20)

4. H. Qi, P. T. Kuruganti, Z. Liu, "Early detection of breast cancer using thermal texture maps," *IEEE International Symposium on Biomedical Imaging: Macro to Nano*, Washington, D. C., July, 2002. (page 21-24)

5. H. Qi, J. F. Head, "Asymmetry analysis using automatic segmentation and classification for breast cancer detection in thermograms," *IEEE Engineering in Medicine and Biology Society Annual Conference (EMBS)*, Istanbul, Turkey, October, 2001. (page 25-28)

6. Curriculum Vita for Dr. Hairong Qi (page 29-35)

Asymmetry Analysis in Breast Cancer Detection Using Thermal Infrared Images*

Phani Teja Kuruganti[1], Hairong Qi[1]

Abstract—**Automated diagnostic tools always provide the doctors with the very valuable second opinion during disease diagnosis. This paper discusses an automated approach for breast cancer detection using Thermal Infrared (TIR) images. Breast cancer is a disease in which only the early diagnosis increases the survival hope. The cancer cells with their higher metabolic rate are hotter than the normal cells and this property makes the cancerous tumors appear as hotspots in the TIR images. The existence of asymmetry in temperature distribution indicates the existence of tumor. In this paper, we initially segment the breast part of the TIR image using the Hough transform of a parabola. Upon segmentation, different features are extracted from the breast segments. Comparison of these features is done to detect any asymmetry and thus classify the image as cancerous or non-cancerous. The segmentation and feature extraction are performed on the images obtained from Bioyear Inc.**

I. Introduction

Different kinds of diagnostic imaging techniques exist in the field of breast cancer detection. In contrast to traditional invasive X-ray imaging, we use a non-invasive imaging technique, called TIR imaging, as the diagnostic tool. The cancerous cells, due to their high metabolic rates, are at a higher temperature than the normal cells around it. Thus the cancer cells can be imaged as hotspots in the infrared images. The thermogram can provide more dynamic information of the tumor since the tumor can be small in size but can be fast growing making it appear as a high temperature spot in the thermogram [1], [7]. Keyserlingk *et al.* [4] reported that the average tumor size undetected by thermal imaging is 1.28cm and 1.66cm by mammography. It is also reported that the results of thermography can be correct 8-10 years before mammography can detect a mass in the patient's body [2], [5]. Since it is not practically possible to have the tumor symmetrically in both the breasts, exploiting this asymmetry can provide accurate diagnosis result. The main objective of this work is to evaluate the viability of TIR imaging as a non-invasive breast cancer imaging modality. This paper discusses about how the identification of the asymmetry can be automated using different techniques.

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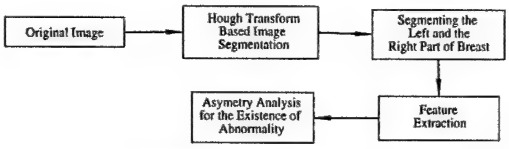

Fig. 1. Algorithm for the asymmetry analysis.

II. Approach

Figure 1 shows a block diagram of different steps that are implemeted in this paper: (1) Edge detection and Hough transform based image segementation; (2) Feature extraction; and (3) Asymmetry analysis to detect the existence of asymmetry automatically.

• *Hough Transform Based Image Segmentation*: Hough transform is an image segmentation technique applied to the image if particular geometric shapes are looked for. The lower part of the edge image of patient's breasts is approximated to the shape of a parabola[6]. Thus, Hough transform for the parabola [3] is used to segment the breasts. Figure 2 shows some examples of the segmented images.

• *Feature Extraction*: Feature extraction is performed on the segmented pseudo-colored TIR images. The aim of this research is to identify the effectiveness of the features in contributing towards the asymmetry analysis.

– *Moments of the intensity image*: The moments of the histogram gives the statistical information of the texture of the image. The four moments, mean, variance, skewness, and kurtosis are taken as features.

– *The peak pixel intensity of the correlated image*: We use the peak intensity of the correlated image as a feature element since the higher the correlation value, the more symmetric the two breast segments.

– *Entropy*: It measures the uncertainty or the information contained in the segmented images. The more equal the intensity distribution, the more entropy. Therefore, the segment with hot spots should have a lower Entropy.

– *Joint Entropy*: The higher the joint entropy between the left and right breast segments, the more the symmetry.

• *Asymmetry Analysis*: From the above set of features derived from the testing images, the existence of asymmetry is decided by calculating the ratio of the feature from the left and right segment. The closer the value to 1, the more correlated the features or the less asymmetric the segments.

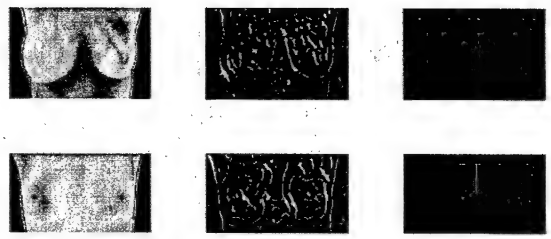

Fig. 2. Hough transform based image segmentation. Top: cancerous image. Bottom: non-cancerous image. From left to right: the original TIR image, the edge image using Canny edge detector, the segmentation based on Hough transform.

Moments	*cancerous*		*non-cancerous*	
	Left	Right	Left	Right
Mean	0.0010	0.0008	0.0012	0.0010
Variance (10^{-6})	2.0808	1.1487	3.3771	2.7640
Skewness (10^{-6})	2.6821	1.1507	4.8489	4.5321
Kurtosis (10^{-8})	1.0481	0.3459	2.1655	2.3641

TABLE I

MOMENTS OF THE HISTOGRAM.

Feature	*cancerous*		*non-cancerous*	
Correlation	2.500×10^8		2.357×10^8	
Joint Entropy	9.0100		17.5136	
Entropy	Left	Right	Left	Right
	1.52956	1.3033	1.70684	1.4428

TABLE II

ENTROPY AND CORRELATION VALUES.

III. Experimental Results and Analysis

The testing images are obtained from Bioyear Inc., with a sensitivity of 0.05 degree celsius. Figure 2 shows the segmentation results.

The typical values of the cancerous images and non-cancerous images are tabulated in Table II. The asymmetry can be clearly stated with a close observation of the above feature values. We used 6 normal patient thermograms and 18 cancer patient thermograms.

Figure 3 evaluates the effectiveness of the features used. The first data point along the x-axis indicates *entropy*, the second to the fifth points indicate the four statistical moments (*means, variance, skewness, and kurtosis*). The y-axis shows the *closeness* metric we defined as

$$\text{Bilateral ratio closeness to 1} = \left|\frac{\text{feature value from left segment}}{\text{feature value from right segment}} - 1\right| \quad (1)$$

From the figure, we observe that the high-order statistics

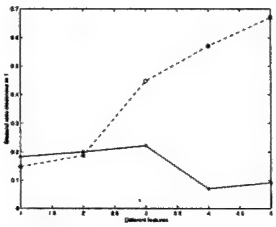

Fig. 3. Performance evaluation of different feature elements. Solid line: non-cancerous image; Dash line: cancerous image. The five data points along the x-axis indicate (from left to right): entropy, mean, variance, skewness, kurtosis.

are the most effective features to measure the asymmetry, while low-order statistics (*mean*) and *entropy* do not assist asymmetry detection.

IV. Conclusion

This paper describes a computer based approach for automating the asymmetry analysis of the thermograms. From the experimental results, it can be observed that the Hough transform can be effectively used for breast segmentation and the derived features can be used for asymmetry analysis. These kind of diagnostic aids, especially in a diseases like breast cancer where the reason for the occurence is not totally known, will reduce the false positive diagnosis rate and increase the survival rate among the patients since the early diagnosis of the disease is more curable than in a later stage.

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Breast Cancer Identification through Shape Analysis in Thermal Texture Maps

Hairong Qi[1] Zhongqi Liu[2], Chen Wang[2]

Abstract—**This paper proposes an automated approach to the study of metabolic activities within a human body using thermal infrared (TIR) imaging. It uses early detection of breast cancer as an example to show the effectiveness of the approach. Different shape analysis parameters are employed in the development.**

I. Introduction

In an earlier paper [2], we described the usage of thermal infrared imaging (TIR) in early detection of breast cancer. We used the term *thermal texture maps* to represent the images captured from TIR imaging. A *thermal-electric analog* was used to analyze a thermal system to avoid solving the inverse problem of Pennes' bio-heat equation. Based on this analog, the depth of the heat source can be estimated by looking for the half power point through slicing. If we assume the distribution of the surface temperature can be modeled as Gaussian, then we can slice the Gaussian from top to bottom at a fixed interval. The increment of the radius in the horizontal direction between adjacent slices would not have dramatic change until the half power point is crossed. Slicing is in essence a thresholding process, where all pixels with a temperature higher than the slicing temperature (the threshold) are assigned a pseudo-color *white*. Therefore, by slicing (decreasing) the surface temperature at a certain degree per step, and by observing the growth pattern of the white pixels, we can find the half power point.

The concept has helped tremendously in understanding the metabolic activities undergoing within the human body. Besides measuring the depth of the heat source, slicing can also reveal the growth pattern of the white pixels. For example, the pixels of lymph nodes and tumors should grow in a circular pattern, while the growth pattern of blood vessel is along the direction of the blood vessel. The technique and the resulting apparatus have been patented [1]. The system has been used in early detection of breast cancer. Clinical study has shown increased sensitivity and specificity.

Even though the concept is very effective, the detection of the half power point is still relied mostly on human observation. In another word, by just "looking" at the amount of growth of white pixels between adjacent slices, the radiologists make a decision whether a specific slice has crossed the half power point and thus derive the depth of the heat source. Similarly, by observing the growth pattern of the white pixels, different tissues within the human body can be identified as well. The biggest problem with human-based diagnosis is its inconsistency among different radiologists and the amount of time spent in diagnosis.

In this paper, we use a synthetic example to demonstrate how slicing works and the effectiveness of an automatic approach for the detection of half power point based on shape analysis.

II. Automatic Detection of Half Power Point

Figure 1 shows a synthetic example of how slicing works. The image is taken from a piece of pork fat. An electric bulb is lit and inserted at the center of the pork fat as a heat source such that we can control the location of the heat source. "White" represents the highest temperature and "black" the lowest. First of all, an appropriate temperature needs to be found such that white pixels at the center of the pork fat start to show up in the next slice. We use "initial state" to refer this image. Each of the following slicing process decreases the highest temperature in the color-map by 0.1°C (e.g. the threshold is lowered by 0.1°C), such that more white pixels can appear. If we come to a point where the increment of the white pixel is dramatic, the half power point is the slice before it. In the example, the increment of the radius of the white cluster is much larger between slice 3 and 4 than previous increments. The depth of the bulb is thus 3cm, which is the same as the ground truth.

Even though the ground truth in the above simulation says that the heat source is 3cm in depth, and that *experienced* radiologists are able to identify it at the right slice, it is still hard to convince most observers why the half power point is not at slice 1 or slice 2 since the growth of white pixels can also be described as "dramatic" depending on what your definition of "dramatic" is. In another word, there is quite a bit of ambiguity existed in the diagnosis. A quantitative measurement of the growth rate is needed to provide more objective criteria for deriving the depth of the heat source. We still use the synthetic experiment as an example to show how the automated approach works. We derive several shape descriptors and study the change of these descriptors over slices to help identify the

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Fig. 1. Different slices from the pork fat experiment.

half power point.

A. Thinness

There are two definitions for thinness (T_a and T_b): $T_a = P^2/A - 4\pi$, and $T_b = D/A$. P, D, and A are the *perimeter*, *diameter*, and *area* of the segment, respectively. Perimeter is a count of all pixels in the segment that are adjacent to a pixel not in the segment. Diameter describes the maximum chord - the distance between those two points on the boundary of the segment whose mutual distance is maximum [3]. Here, we use the length of the major axis to estimate the diameter. Area is a count of all pixels within the segment.

B. Minimum Aspect Ratio (MAR)

MAR is the length/width ratio of the minimum bounding rectangle of the segment. We use the ratio between the length of major axis and minor axis to estimate the MAR.

C. Principal Component Analysis (PCA)

PCA is a popular method used to derive the major axis and minor axis of a segment. The axes are characterized by the eigenvectors (direction of the axes) and eigenvalues (length of the axes) of the covariance matrix of the segment. The growth rate of the major axis can be used to identify the half power point, while the thinness and MAR can be used to describe the shape of the heat source. The shape of blood vessels should have a much larger thinness and MAR measurements than the shape of a tumor.

III. Experimental Results

We first calculate the *length of the major axis* to study the growth pattern of the heat source between different slices, as shown in Fig 2. We can see that the length increases linearly from slice one to slice two to slice three. Between slice three and slice four, the increasing rate (or the slope of the line segment) is much larger than those of the first three slices. Therefore, by comparing the growth rate of the length of the major axis, we can have a very effective and objective criterion.

We then calculate the *thinness* and *MAR* of the heat source between slices. These two profiles, along with the length of major axis are shown in Fig. 3. From the three

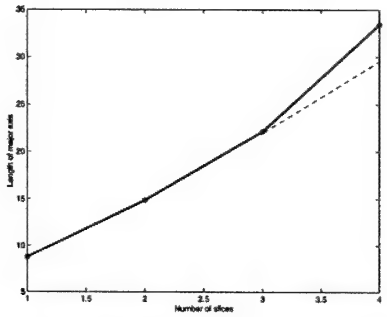

Fig. 2. The length of the major axis vs. different slices. Note: the dash line is plotted for comparison. The slope of the line segments is the growth rate.

profiles, we can see that for potential tumors, the MAR stays roughly the same, while thinness changes irregularly.

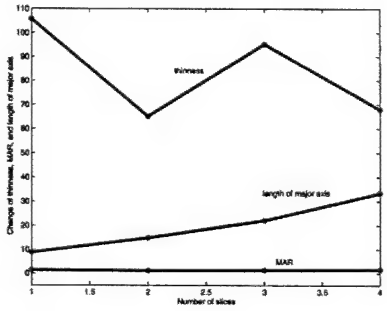

Fig. 3. Change of thinness, MAR and major axis vs. slices.

IV. Summary

Automated detection of the depth of heat source is a challenging problem. First of all, a segmentation algorithm needs to be developed to identify the heat source. Then shape analysis techniques can be deployed to characterize the growth pattern. However, human body is a very complicate biological object, different tissues overlap with each other, making it difficult for segmentation. Some preliminary results reported in this paper show the effectiveness of using shape analysis to automate the detection of half power point and thus the depth of the heat source.

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DETECTING BREAST CANCER FROM THERMAL INFRARED IMAGES BY ASYMMETRY ANALYSIS

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This project started in August, 2001. It is a research effort that helps define thermal infrared (TIR) imaging as a diagnostic tool in early detection of breast cancer, which can be used as a complementary to traditional mammography.

Research has shown that if detected earlier (tumor size less than 10mm), the breast cancer patient has an 85% chance of cure as opposed to 10% if detected late. TIR imaging, as a non-invasive, non-ionizing imaging modality, can provide functional information about the cancer cell that is not easily measured by other methods like X-ray radiology and CT that primarily provide information on the anatomical structures.

TIR images the heat emanating from the heat source, transported by the radiation and picked up by the Infrared (IR) on the surface. Cancerous tissue absorbs 5 – 10 times more glucose and liberates less energy than the normal cells. The high metabolic activity keeps the cancer cell at a higher temperature than the normal cell. Therefore, tumors of the breast induce abnormalities in skin temperature which can be detected by TIR.

One of the popular methods for breast cancer detection is to make comparisons between contralateral images. When the images are relatively symmetrical, small asymmetries may indicate a suspicious region. In TIR imaging, asymmetry analysis normally needs human interference because of the difficulties in automatic segmentation. In order to provide a more objective diagnosis result, we propose an automatic approach to asymmetry analysis in thermograms. It includes automatic segmentation and supervised pattern classification. Hough transform is used to extract the four feature curves (the left and right body boundaries and the parabolic-shaped lower boundaries of the breasts) that uniquely segment the left and right breasts. Upon segmentation, statistical features (moment measurements of the local histogram) are derived from both segments. Ratios between the corresponding feature values from each segment are used as inputs to the supervised learning methods (k-Nearest-Neighbor and Maximum Posteriori Probability) for classification.

Experiments have been conducted based on images provided by Elliott Mastology Center (Inframetrics 600M camera) and Bioyear, Inc. (Microbolometer uncooled camera).

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Early Detection of Breast Cancer using Thermal Texture Maps

Hairong Qi[1], Phani Teja Kuruganti[1], Zhongqi Liu[2]

Abstract— **This paper focuses on the discussion of using thermal infrared imaging (TIR) in early detection of breast cancer. We use the term *thermal texture maps* to represent the images captured from TIR imaging. Even though the heat emanating onto the surface from the cancerous tissue can be successfully modeled using the Pennes bio-heat equation, the complexity of the boundary conditions associated with the biological body makes it impractical to solve the inverse problem. This paper presents a new method for analyzing a thermal system based on an analogy to electrical circuit theory; referred to as *thermal-electric analog*. We demonstrate how the analog can be used to estimate the depth of the heat source, and furthermore, help understand the metabolic activities undergoing within the human body. The method has been used in early breast cancer detection and has achieved high sensitivity. Several breast cancer study cases are given to show the effectiveness of the method. On-going clinical study results are provided as well.**

I. Introduction

Temperature is a long established indicator of health. The Greek physician, Hippocrates, wrote in 400 B.C. that "*In whatever part of the body excess of heat or cold is felt, the disease is there to be discovered* [8]." Before Galileo invented thermoscope, the ancient Egyptians used fingers as scanners to monitor the surface temperature of the human body [8]. Modern development of the temperature measurement has been in the area of thermal infrared (TIR) imaging which does not need body contact. Based on FDA's definition, TIR imaging measures the heat emanating from the heat source transported by radiation.

Infrared (IR) radiation occupies the region on the electromagnetic spectrum between visible and microwaves. All objects in the universe emit radiations in the IR region as a function of their temperature. As an object gets hotter, it gives off more intense infrared radiation, and it radiates at a shorter wavelength [3]. Human eye cannot detect IR rays, but they can be detected using the thermal infrared cameras and detectors.

TIR imaging has been applied to a wide spectra of applications, ranging from the military, industrial engineering, to modern medicine. It is non-invasive and non-destructive, which makes it a valuable tool to assist diagnosis.

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This paper focuses on the discussion of using TIR imaging in early detection of breast cancer. We use the term *thermal texture maps* to represent the images captured from TIR cameras. The application of IR imaging in breast cancer study starts as early as 1961 when Williams and Handley first published their results in the *Lancet* [6]. However, the premature use of the technology and its poorly controlled introduction of into breast cancer detection in the 70s have led to its early demise [4]. IR-based diagnosis was criticized to generate a higher false-positive rate than mammogram, and thus was not recommended as a standard modality for breast cancer detection. Therefore, despite its deployment in many areas of industry and military, IR usage in medicine has declined [3]. Thirty years later, several papers and studies have been published to reappraise the use of IR in medicine [4], [3] for the following three reasons: 1) We have much more improved infrared technology. New generations of IR cameras have been developed with much enhanced accuracy; 2) We have much better capabilities in image processing. Advanced techniques including image enhancement, restoration and segmentation have been effectively used in processing IR images; and 3) We have a deeper understanding of IR images based on the patho-physiological approach.

Infrared imaging is a physiological test that measures the physiology of the blood flow and behavior of the nervous system by means of precise temperature measurement. Unlike imaging techniques such as X-ray radiology and CT that primarily provide information on the anatomical structures, IR imaging provides functional information not easily measured by other methods. Thus correct use of IR images requires in-depth physiological knowledge for its effective interpretation.

All objects at temperature above absolute zero emit electromagnetic radiation spontaneously, called the *natural thermal radiation* [3]. The heat emanating on to the surface from the cancerous tissue and the surrounding blood flow can be quantified using the Pennes' bioheat equation [7]. This equation includes the heat transfer due to conduction through the tissue, the volumetric metabolic heat generation of the tissue, and the volumetric blood perfusion rate whose strength is considered to be the arterio-venous temperature difference. The equation is given as:

$$k\Delta^2 T - c_b w_b (T - T_a) + q_m = 0 \qquad (1)$$

where k is conductivity, q_m is volumetric metabolic rate of the tissue, $c_b w_b$ is the product of the specific heat capacity and the mass flow rate of blood per unit volume of tissue, T is the unknown tissue temperature, and T_a is the arterial temperature.

In theory, given the heat emanating from the surface of the body measured by IR imaging, by solving the inverse heat transfer problem, we can obtain the heat pattern of various internal elements of the body. Different methods of solving the bio-heat transfer equation have been presented in literature [1], [2]. Although it is possible to calculate the thermal radiation from a thermal body by thermodynamics, the complexity of the boundary conditions associated with the biological body makes this approach impractical.

This paper presents a new method for analyzing a thermal system based on an analogy to electrical circuit theory; referred to as *thermal-electric analog*. We demonstrate how the analog can be used to estimate the depth of the heat source, and furthermore, help understand the metabolic activities undergoing within the human body. The method has been used in early breast cancer detection and has achieved high sensitivity. Several breast cancer study cases are given to show the effectiveness of the method. On-going clinical study results are provided as well.

II. The Thermal-Electric Analog

As the living cells within a biological body are constantly undergoing metabolic activities, the biochemical and the physical metabolic processes generate heat. Thus the amount of radiation on the surface of the human body can reflect its metabolic rate. The theory underlying conventional thermographic techniques as applied to cancer is that the change of the pulse distribution around a cancerous area and the rate of metabolism are greater than the general tissue, resulting in a higher temperature at the skin surface [5].

Even though the temperature of the skin surface can be measured, if the relationship between the surface temperature and the emissions from inside of the body cannot be established, the application of TIR imaging technique is still limited. Pennes' bio-heat equation models the process of heat transfer but has its limits in practice. Thus, a new method that does not require a direct solution to the inverse heat transfer problem, the thermal-electric analog, comes into light.

Figure 1 illustrates the analogy between thermodynamics systems and the electrical circuit, where the heat source S inside the human body can be simulated as a battery with voltage U_S, the heat loss inside the heat source can be

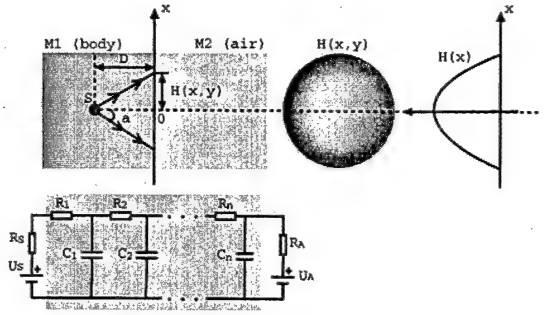

Fig. 1. The thermal-electric analog.

simulated as the heat loss on a resistor R_S. The *temperature* of the heat source can then correspond to the *voltage* of the battery, and the *heat current* to the *circuit current*. Similarly, we can map the heat source in the air (outside the human body) as U_A, and the heat loss as R_A. The set of R_i's and C_i's correspond to the unit heat resistance and heat capacity along each radiation line. The circuit in Fig. 1 only shows the analogy for one radiation line. In the study of breast cancer, it is reasonable to assume that the medium between the heat source (S) and the surface is homogeneous. Therefore, the radiation pattern sensed by the IR camera at the surface should have a distribution like Gaussian as shown in Fig. 1. The surface temperature $H(x,y)$ corresponds to the output voltage $U(x,y)$ can then be calculated by Eq. 2.

$$U(x,y) = U_S - \frac{\sum_{i=1}^{n} R_i}{R_S + R_A + \sum_{i=1}^{n} R_i} \times (U_S - U_A) \quad (2)$$

and

$$n = \lfloor \frac{D}{R_0 \cos a} \rfloor, a = \arctan \frac{D}{\sqrt{x^2 + y^2}}$$

where $\lfloor m \rfloor$ represents the largest integer less than m, n is the number of resistors used in the circuit, D is the depth of the heat source, and R_0 is the unit heat loss (or the *heat resistance rate*) in a certain medium. Different parts of human body have different heat resistance rate, as shown in Table I.

body parts	heat resistance rate
fatty tissue	0.1 - 0.15°C/cm
muscle	0.2°C/cm
bone	0.3 - 0.6°C/cm

TABLE I
Heat resistance rate of different body parts.

The thermal-electric analog provides a convenient way to estimate the depth of the heat source.

A. Estimation of the Depth of the Heat Source

The depth estimation is based on the assumption that we can use Gaussian to model the distribution of the surface temperature. Half power point is a useful property of Gaussian distribution. It divides the total power enclosed by the Gaussian into equally half. Therefore, if the temperature (or voltage) at the maximum of the Gaussian is T (or U), then the temperature (or voltage) at the half power point is $T/\sqrt{2}$ (or $U/\sqrt{2}$) as shown in Fig. 2. According to Eq. 2, we can derive the angle a that leads to the half power point is approximately equal to $\pi/4$. Therefore, in the right triangle formed by SAB, $SA = AB$ where SA is the depth of the heat source and AB is the distance between the maximum of the Gaussian and the half power point. In another word, if we can find the half power point, we can derive the depth of the heat source.

If we slice the Gaussian from top to bottom at a fixed interval, the increment of the radius in the horizontal direction would not have dramatic change until the half power point is crossed. From Fig. 2, we can see that the relative increment of the radius between the first slice and the second slice is 34 pixels, and 40 pixels between the second slice and the third slice, but 116 pixels between the third slice and the fourth slice. Therefore, the half power point is at the position of the third slice. Each slice of the Gaussian curve corresponds to a temperature deduction of 0.1°C. For the application of breast cancer detection, based on the heat resistance rate of fat tissues, the 0.1°C temperature drop occurs over a 1cm distance. Therefore, by slicing (decreasing) the surface temperature at a certain degree per step, we can find the half power point with the accuracy at the level of centimeter ($AB = \Delta T/R_0$ where R_0 is the heat resistance rate).

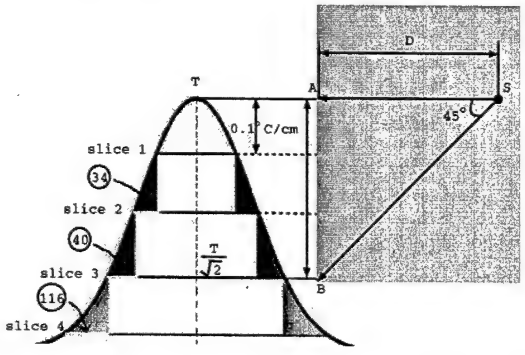

Fig. 2. Illustration of half power point of Gaussian and the depth of the heat source.

III. Experimental Results and Analysis

A. Simulation Results

Figure 3 shows a synthetic example of how slicing works. The image is taken from a piece of pork fat. An electric bulb is lit and inserted at the center of the port fat as a heat source such that we can control the location of the heat source. The pseudo color-map is also shown in the figure. "White" represents the highest temperature and "black" the lowest. First of all, an appropriate temperature needs to be found such that white pixels at the center of the pork fat starts to show up in the next slice. We use "initial state" to refer this image. In this example, the initial state is when the temperature is 20.50°C. Each of the following slicing process decreases the highest temperature in the color-map by 0.1°C (e.g. the threshold is lowered by 0.1°C), such that more white pixels can appear. If we come to a point where the increment of the white pixel is dramatic, the half power point is the slice before it. In the example, the increment of the radius of the white cluster is much larger between slice 3 and 4 than previous increments. The depth of the bulb is thus 3cm, which is the same as the ground truth.

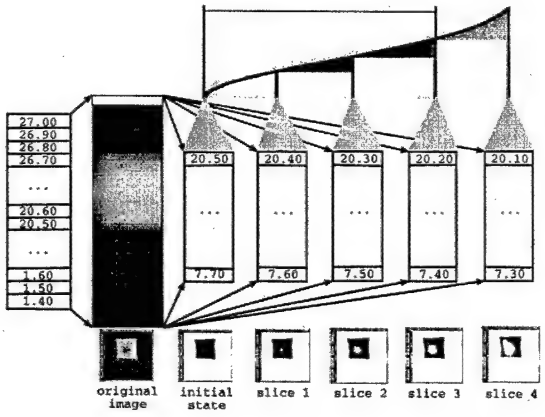

Fig. 3. Simulation of slicing operation on pork fat.

B. Patient Data Analysis

Besides measuring the depth of the heat source, slicing can also reveal the growth pattern of the white pixels. Different tissues have different growth patterns. By observing this pattern, different tissues can be distinguished as well. For example, the pixels of lymph nodes and tumors should grow in a circular pattern, while the growth pattern of blood vessel is along the direction of the blood vessel.

A diagnosis protocol has been designed for early breast cancer detection. Six steps are involved in this protocol:

- Step 1: Growth pattern of lymph nodes in the armpits
- Step 2: Size of the abnormal area
- Step 3: Appearance of the abnormal area
- Step 4: Vascular pattern
- Step 5: Nipples and areola pattern
- Step 6: Dynamic diagnosis with outside agents (antibiotic, etc.)

Take the first step as an example, if the lymph nodes in the armpits reveal one heat source with a depth less than 2cm, one abnormal sign (+) will be recorded; if two heat sources appear with a depth less than 2cm and a bilateral temperature difference greater than 0.2 degree, then two abnormal signs (++) will be recorded, etc.

Figure 4 shows a patient with lobular carcinoma in the left breast. From slicing, we observe the following abnormal signs:

1. 2cm tumor surrounded by 4 blood vessels (+++);
2. White pixels surround the nipple in 3 slices (+++);
3. Nipple bilateral temperature difference is 0.8°C (+).

Fig. 4. Slicing of patient with lobular carcinoma in the left breast.

Figure 5 shows a patient diagnosed to have ductal carcinoma in her left breast. From slicing, we observe the following abnormal signs:

1. Lymph node bilateral temperature difference is 0.8°C (++++);
2. The tumor is 2cm from the surface (++);
3. The tumor is surrounded by five blood vessels (+++);
4. It takes less than three slices to have the white pixels surround the nipple (++).

Fig. 5. Slicing of patient with ductal carcinoma in the left breast.

IV. Summary

Slicing is not a new technique. Radiologists have been using slicing to observe IR images all the time. The innovations of this paper lie in the fact that it first reveals the relationship between the pattern in each slice with the metabolic activities within a patient's body. Using thermal-electric analog and half power point to estimate the depth of tumor is just one way to reveal this relationship. This technique and the resulting apparatus have been patented [5]. We refer to the system as Bioyear system or the Texture Mapping Imaging (TMI) system. Clinical study has shown increased sensitivity and specificity. The concept has been validated in China for several applications, including breast cancer detection, ovarian cancer detection. About 400,000 patients were scanned using the Bioyear system in five years. Among them, 50,000 patients did breast scan. There are 103 breast cancer cases detected by TMI were proved by biopsy. Among these 103 cases, 92 cases also went through mammography. Mammography missed 6 out of these 92 cases. 2 of the missed tumor size is 2mm. The concept is also in the process of validation in US and Canada, including the Ville Marie Breast and Oncology Center in Canada, the Elliott Mastology Center at Baton Rouge, LA, and NIH (Karposi Sarcoma / Angiogenesis). The system is also used for ovarian cancer detection. Of the 77 cases studied, the error rate of IR is 6% compared to the error rate of ultrasound or CT scan which ranges from 3% to 5% where body contact is needed and is a painful process.

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Asymmetry Analysis Using Automatic Segmentation and Classification for Breast Cancer Detection in Thermograms

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Abstract— **Thermal infrared imaging has shown effective results as a diagnostic tool in breast cancer detection. It can be used as a complementary to traditional mammography. Asymmetry analysis are usually used to help detect abnormalities. However, in infrared imaging, this cannot be done without human interference. This paper proposes an automatic approach to asymmetry analysis in thermograms. It includes automatic segmentation and pattern classification. Hough transform is used to extract the four feature curves that can uniquely segment the left and right breasts. The feature curves include the left and the right body boundary curves, and the two parabolic curves indicating the lower boundaries of the breasts. Upon segmentation, unsupervised learning technique is applied to classify each segmented pixel into certain number of clusters. Asymmetric abnormalities can then be identified based on pixel distribution within the same cluster. Both segmentation and classification results are shown on images captured from Elliott Mastology Center.**

Keywords— **asymmetry analysis, breast cancer detection, thermogram, Hough transform, pattern classification, unsupervised learning**

I. Introduction

Making comparisons between contralateral images are routinely done by radiologists. When the images are relatively symmetrical, small asymmetries may indicate a suspicious region. This is the underlying philosophy in the use of asymmetry analysis for mass detection in breast cancer study [2]. Unfortunately, due to various reason like short of radiologists, fatigue, carelessness, or simply because of the limitation of human visual system, these small asymmetries might not be easy to detect. Therefore, it is important to design an automatic approach to eliminate human factors.

There have been a few papers addressing techniques for asymmetry analysis of mammograms [2], [7], [8], [9], [10], [11]. [3], [5] recently analyzed the asymmetric abnormalities in infrared images. In their approach, the thermograms are segmented first by operator. Then breast quadrants are derived automatically based on unique point of reference, i.e. the chin, the lowest, rightmost and leftmost points of the breast. In an earlier paper we published [6], Hough transform is used to segment the image, and curvature analysis is proposed to identify the abnormalities. This paper extends our work on using Hough transform for segmentation. New experimental results are provided. Instead of using curvature analysis which is very sensitive to noise, this paper describes a pattern classification approach which uses unsupervised learning to identify abnormalities. k-means algorithm is applied on the segmented images.

Testing images are obtained using the Inframetrics 600M camera, with a thermal sensitivity of 0.05^0K.

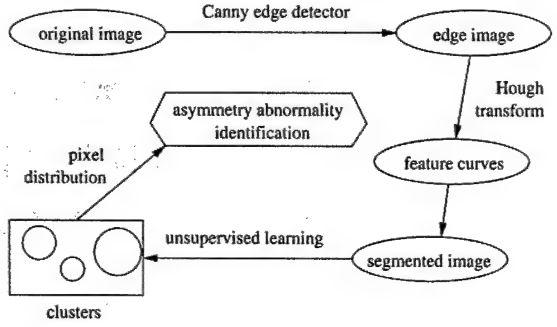

Fig. 1. Procedure of automatic asymmetry analysis of thermogram.

II. Approach

Figure 1 is a block diagram of the five procedures involved in the proposed approach: (1) *Edge image* detection by Canny edge detector; (2) *Feature curve* extraction including the left and right body boundary curves, and the two lower boundaries of the breasts. Hough transform is used to detect the parabolic shaped lower breast boundaries; (3) *Segmentation* based on the intersection of the two parabolic curves and the line formed by the two armpits; (4) *Pattern classification* using unsupervised learning to group each pixel of the segments into certain clusters; and (5) *Pixel distribution* of each cluster is analyzed and abnormalities can then be identified.

A. Edge detection by Canny edge detector

Edge image is first derived by using Canny edge detector [1]. The standard deviation is chosen to be equal to 2.5 so that only strong edges are detected.

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B. Feature curve extraction by Hough transform

There are four dominant curves appeared in the edge image which we called the feature curves: the left and right body boundaries, and two lower boundaries of the breasts. The body boundaries are easy to detect. Difficulties lie in the detection of the lower boundaries of the breasts. We observe that the breast boundaries are generally in parabolic shape. Therefore, Hough transform [4] is used to detect the parabola.

C. Segmentation

Segmentation is based on three key points: the two armpits (P_L, P_R) derived from the left and right body boundaries by picking up the point where the largest curvature occurs, and the intersection (O) of the two parabolic curves derived from the lower boundaries of the breasts. The vertical line that goes through point O and is perpendicular to line P_LP_R is the one used to separate the left and right breasts.

D. Unsupervised learning

Pixel values in a thermogram represent the thermal radiation resulting from the heat emanates from the human body. Different tissues, organs and vessels have different amount of radiation. Therefore, by observing the heat pattern, or in another word, the pattern of the pixel value, we should be able to discover the abnormalities if there are any.

Usually, in pattern classification algorithms, a set of training data are given to derive the decision rule. All the samples in the training set have been correctly classified. The decision rule is then applied to the testing data set where samples have not been classified yet. This classification technique is also called supervised learning. In unsupervised learning, however, data sets are not divided into training sets or testing sets. No *a-priori* knowledge is known about which class each sample belongs to.

In asymmetry analysis, none of the pixels in the segment knows its class in advance, thus there will be no training set or testing set. Therefore, this is an unsupervised learning problem. We use k-means algorithm to do the initial clustering. k-means algorithm is described as follows:

1. Begin with an arbitrary set of cluster centers and assign samples to nearest clusters;
2. Compute the sample mean of each cluster;
3. Reassign each sample to the cluster with the nearest mean;
4. If the classification of all samples has not changed, then stop, else go to step 2.

E. Within cluster pixel distribution

After each sample is relabeled to a certain cluster, the cluster mean can then be calculated. The segmented image can also be displayed in labeled format. From the difference of mean distribution, we can tell if there is any asymmetric abnormalities.

III. Experimental Results

Testing images are obtained using the Inframetrics 600M camera, with a thermal sensitivity of 0.05^0K. The image are collected at Elliott Mastology Center. Results from two testing images (lr, nb) are shown here.

Figure 2 shows the intermediate results from edge detection, feature curve extraction, to segmentation. From the figure, we can see that Hough transform can derive the parabola at the accurate location.

Figure 3 provides the histogram of pixel value from each segment with 10-bin setup. We can tell just from the shape of the histogram that lr shows a more apparent abnormalities than nb. However, histogram only reveals global information.

Figure 4 displays the classification results for each segment in its labeled format. Here, we choose to use four clusters. The figure also shows the mean difference of each cluster in each segmented image. From Fig. 4, we can clearly see the much bigger difference shown in the mean distribution or image lr which can also be observed from the labeled image.

IV. Conclusion

This paper describes an automatic approach for asymmetry analysis in thermograms to help identify abnormalities. It includes an automatic segmentation using Hough transform and an unsupervised pattern classification for segment comparison. From the experimental results, we can see that Hough transform can accurately extract the feature curves, and k-means algorithm provides useful information in the analysis of abnormalities.

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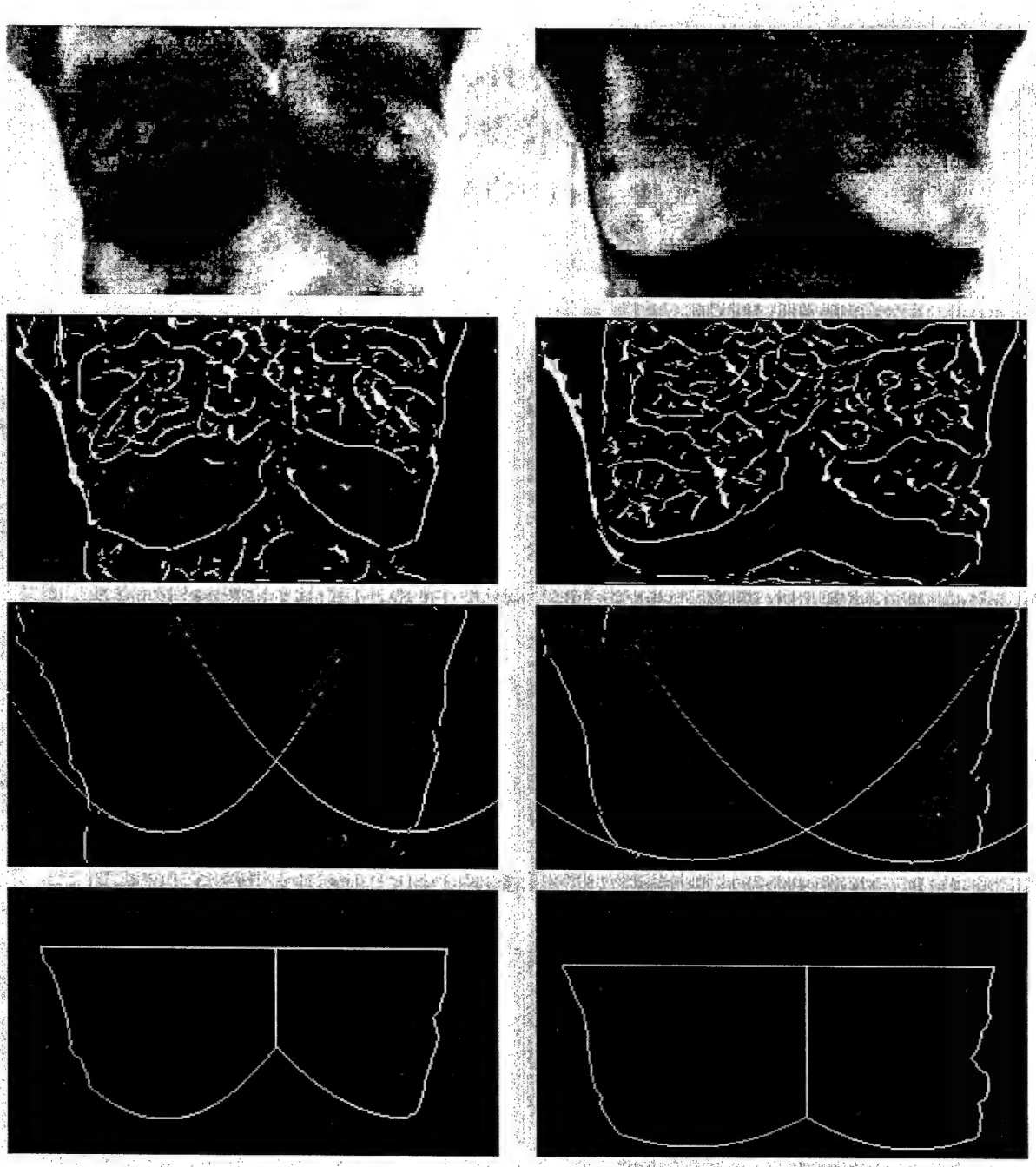

Fig. 2. Segmentation results of two images. Left: results from *lr*. Right: results from *nb*. From top to bottom: original image, edge image, four feature curves, segments.

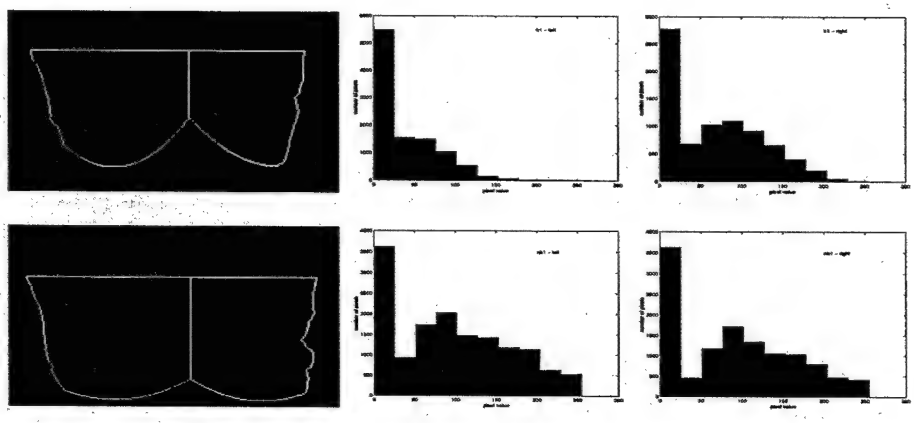

Fig. 3. Histogram of the left and right segments. Top: results from *lr*. Bottom: results from *nb*. From left to right: the segments, histogram of the left segment, histogram of the right segment.

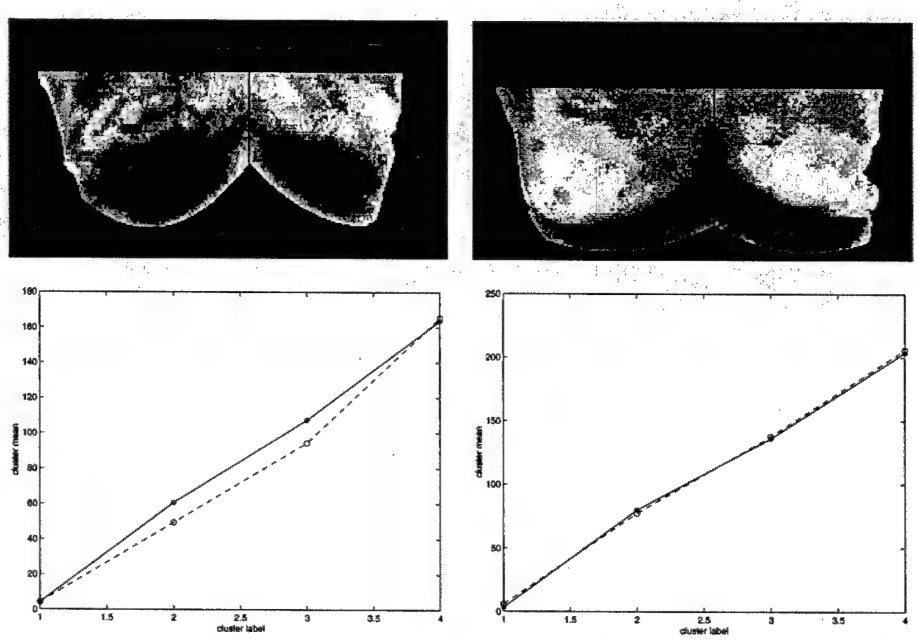

Fig. 4. Labeled image and the profile of mean for each cluster. Left: results from *lr*. Right: results from *nb*. Top: labeled image. Bottom: average pixel value profile of each cluster

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ECE310 Signals and Systems (S'01, Su'00)

ECE453 Computer Networking Design (F'02)

ECE644 Information Theory (S'02)

ECE599 Internet Protocols (F'01, F'02)

ECE205 Electrical Engineering Computation (S'00, F'99)

All course related materials can be located at `http://aicip.ece.utk.edu/teaching.html`.

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Principal Investigator, "Detecting Breast Cancer from Thermal Infrared Images by Asymmetry Analysis." Funded by *U.S. Army Medical Research and Materiel Command (USAMRMC), Department of Defense Breast Cancer Research Program, Concept Award.* August 2001 - January 2003. $69,841.

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H. Qi, Z. Qi, C. Wang, "Breast cancer identification through shape analysis in thermal texture maps," *EMBS-BMES*, October 2002.

P. T. Kuruganti, H. Qi, "Asymmetry analysis in breast cancer detection using thermal infrared images," *EMBS-BMES*, October 2002.

H. Qi, W. E. Snyder, W. A. Sander, "Blind consistency-based steganography for information hiding in digital media," *IEEE International Conference on Multimedia and Expo*, Lausanne, Swizerland, August 26-29, 2002.

X. Wang, H. Qi, "Face recognition using optimal non-orthogonal wavelet basis evaluated by information complexity," *International Conference on Pattern Recognition*, vol. 1, page 164-167, Qubec, Canada, August, 2002.

X. Wang, H. Qi, S. S. Iyengar, "Collaborative multi-modality target classification in distributed sensor networks using mobile agent," *Information Fusion*, pages 285-290, Annapolis, MA, July 2002.

H. Qi, P. T. Kuruganti, Z. Liu, "Early detection of breast cancer using thermal texture maps," *IEEE International Symposium on Biomedical Imaging: Macro to Nano*, Washington, D. C., July, 2002.

H. Qi, "Feature selection and kNN fusion in molecular classification of multiple tumor types," *International Conference on Mathematics and Engineering Techniques in Medicine and Biological Sciences (METMBS)*, Las Vegas, June, 2002.

X. Wang, H. Qi, "Acoustic target classification using distributed sensor arrays," *International Conference on Acoustics Speech and Signal Processing (ICASSP'02)*, Orlando, Florida, May, 2002.

Y. Tian, H. Qi, "Target detection and classification using seismic signal processing in unattended ground sensor systems," *International Conference on Acoustics Speech and Signal Processing (ICASSP'02)*, Orlando, Florida, May, 2002.

H. Qi, J. F. Head, "Asymmetry analysis using automatic segmentation and classification for breast cancer detection in thermograms," *IEEE Engineering in Medicine and Biology Society Annual Conference (EMBS)*, Istanbul, Turkey, October, 2001.

H. Qi, X. Wang, S. S. Iyengar, K. Chakrabarty, "Multisensor data fusion in distributed sensor networks using mobile agents," *Information Fusion*, TuC2-11-16, Canada, August, 2001.

H. Qi, F. Wang, "Optimal itinerary analysis for mobile agents in ad hoc wireless sensor networks," *The 13th International Conference on Wireless Communications*, vol. 1, pp.147-153. Calgary, Canada, July, 2001.

L. M. Tolbert, H. Qi, F. Z. Peng, "Scalable multi-agent system for real-time electric power management," *IEEE Power Electronics Summer Meeting*, July, 2001.

F. Wang, F. Gong, F. Wu, H. Qi, "Design and implementation of property-oriented detection for link state routing protocols," *Proceedings of the 2001 IEEE Workshop on Information Assurance and Security*, pp. 91-99, United States Military Academy, West Point, NY, June, 2001.

K. Chakrabarty, S. S. Iyengar, H. Qi, E. Cho, "Coding theory framework for target location in distributed sensor networks," *IEEE International Conference on Information Technology: Coding and Computing*, April, 2001.

H. Qi, S. S. Iyengar, K. Chakrabarty, "Distributed multi-resolution data integration using mobile agents," *IEEE Aerospace Conference*, vol. 3, pp.1133-1141, Big Sky, Montana, March, 2001.

H. Qi, W. E. Snyder, J. F. Head, R. L. Elliott, "Detecting breast cancer from infrared images by asymmetry analysis," *Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Chicago, July, 2000.

H. Qi, W. E. Snyder, "Conditioning analysis of missing data estimation for large sensor arrays," *IEEE International Conference on Computer Vision and Pattern Recognition*, v2, pp565-570, Hilton Head Island, SC, June, 2000.

W. E. Snyder, H. Qi, W. Sander, "A Hexagonal coordinate system," *SPIE Medical Imaging: Image Processing*, Pt.1-2, pp716-727, February, 1999.

H. Qi, W. E. Snyder, "Lesion detection and characterization in digital mammography by Bezier histograms," *SPIE Medical Imaging: Image Processing*, Pt.1-2, pp1521-1526, February, 1999.

H. Qi, W. E. Snyder, G. L. Bilbro, "Missing data estimation by separable deblurring," *Proceedings for the IEEE International Joint Symposia on Intelligence and Systems*, May, 1998, pp348-353.

H. Qi, W. E. Snyder, G. L. Bilbro, "Comparison of mean field annealing and multiresolution analysis in missing data estimation," *Computer Vision - ACCV'98: Third Asian Conference on Computer Vision*, v1, pp722-729, Hong Kong, China, January 8-10, 1998.

H. Qi, W. E. Snyder, G. L. Bilbro, "Using mean field annealing to solve anisotropic diffusion problems," *IEEE International Conference on Image Processing*, v3, 1997, pp352-355.

Invited Talks

H. Qi, Z. Liu, Z. Wang, "Breast Cancer Identification through Shape Analysis in Thermal Texture Maps," *IEEE Annual EMBS Conference*, Houston, TX, October 24-26, 2002.

H. Qi, P. T. Kuruganti, "Detecting Breast Cancer from Thermal Infrared Images by Asymmetry Analysis," *Era of Hope*, Department of Defense Breast Cancer Research Program Meeting, vol. 1, p15-10, Orlando, FL, September 25-28, 2002.

H. Qi, Z. Liu, "Use of Thermal Texture Maps (TTM) in Breast Cancer Detection - Bioyear Concept," *From Tanks to Tumors: A Workshop on the Applications of IR Imaging and Automatic Target Recognition (ATR) Image Processing for Early Detection of Breast Cancer*, Arlington, VA, December 4-6, 2001.

Dissertation

H. Qi, *A High-Resolution, Large-Area, Digital Imaging System*, Ph.D. Dissertation, North Carolina State University, August, 1999.

GRADUATE STUDENT SUPERVISION

Advisor - Ph.D. students: Xiaoling Wang, Yingyue Xu, Yang Liu.

Advisor - M.S. students: Phani Teja Kuruganti, Hongtao Du, Olawoye Oyeyele.

Advisor - M.S. graduates: Yuxin Tian (Summer, 2001)

Committee Member - Ph.D. candidates: Yan Zhang, David Page, Faysal Boughorbel, J. Patrick McClanahan.

Committee Member - Ph.D. graduates: Yiyong Sun (Fall, 2002), Ambrose Ononye (Fall, 2001), Shaun Gleason (Summer, 2001), Jovan Ilic (Spring, 2001)

Committee Member - M.S. students: Venkatesh Bhaskaran

Committee Member - M.S. graduates: Jason S. Rudisill (Fall, 2002), Andrew R. Wilson (Summer, 2002), Annapoorani Gothandaraman (Fall, 2001), Yupeng Zhang (Summer, 2001), Cheolha Pedro Lee (Spring, 2001), Priyanka Dasgupta (Fall, 2000)

PROFESSIONAL SERVICES AND HONORS

Professional Services

Program Committee and Session Chair on "Distributed Data Mining," *C. Warren Neel Conference on the New Frontier of Data Mining (DM), Knowledge Discovery (KD), and E-Business*, Knoxville, TN, June 22-25, 2002.

Guest Editor, *Distributed Sensor Networks for Real-time Systems with Adaptive Reconfiguration.* Special Issue of *Journal of Franklin Institute*, May, 2001.

Session Chair, *IEEE International Joint Symposia on Intelligence and Systems*, Rockville, Maryland, May 21-23, 1998

Reviewer, *IEEE Transactions on Computers*, 2002.

Reviewer, *Proceedings of the IEEE*, 2002.

Reviewer, *EURASIP Journal on Applied Signal Processing*, 2002.

Reviewer, *Journal of American Society of Information Science*, 2001.

Reviewer, *IEEE Transactions on Knowledge and Data Engineering*, 2001.

Reviewer, *The 9th International Conference on Advanced Computing and Communications (ADCOM)*, 2001.

Reviewer, *IEEE Transactions on Multimedia*, 2000

Reviewer, *The World Multiconference on Systemics, Cybernetics and Informatics (SCI)*, 2000, 2001, 2002

Reviewer, *Optical Engineering*, 1999

Professional Organizations

Member, IEEE *Engineering in Medicine and Biology Society*, 2000 - present; Student Member, 1997 - 1999.

Member, Sigma Xi, 2000 - present

University and Departmental Services

Secretary, *The University of Tennessee Chapter of Sigma Xi*, 2000-2002. Organizing the Annual Sigma Xi Graduate Student Competition.

Judge, *State Science Olympiad Competition*, April, 2001.

Departmental Search Committee Member (Computer Engineering Area, Image Processing Area), 2000, 2001, 2002, 2003.

Departmental Curriculum Committee Member, 2001

Honors and Awards

Science Alliance Faculty Award, University of Tennessee and Oak Ridge National Laboratory, 2001.

January, 2003